An Algorithm for the Optimal Waste Collection in Urban Areas

(Article begins on next page)

An algorithm for the optimal waste collection in urban areas

Edoardo Fadda, Guido Perboli, and Roberto Tadei

Abstract In waste collection, one of the most important decision regards the routing and the scheduling of the service. In this context, during the Optimization for Networked Data in Environmental Urban Waste Collection (ONDE-UWC) project, an innovative optimization method for tackling those decisions has been developed in collaboration with the company Cidiu Spa (www.cidiu.to.it). The importance of the method is three-folds. First, it is innovative because it does not impose periodic routes. Second, it uses information coming from IoT sensors in order to build statistical models for the waste collection evolution. Third, the developed method has shown great usability and performance in the real field.

Key words: Waste Management, Scheduling Heuristic, Routing, Heuristic

1 Introduction

Waste collection in urban areas is a challenging problem due to urbanization and to consumption growth. The citizens of the European Union generate more than 2.3 billion tons of refuse each year. Although municipal waste represents only about 10% of total waste [5], it is of central importance for city livability. Furthermore, the efficiency of the collection services directly influences the tax amount, the emissions of pollutant, the health of citizens and visual pollution. Thus, improving the

Edoardo Fadda
DAUIN, Politecnico di Torino, Torino, Italy, e-mail: edoardo.fadda@polito.it

Guido Perboli
DAUIN, Politecnico di Torino, Torino, Italy, e-mail: guido.perboli@polito.it

Roberto Tadei
DAUIN, Politecnico di Torino, Torino, Italy, e-mail: roberto.tadei@polito.it

efficiency of waste management results in substantial advantages for the whole community.

In this context, this paper presents the results of the project Optimization for Networked Data in Environmental Urban Waste Collection (ONDE-UWC) (http://onde.city). This project was funded by the Regional Council of Piemonte. The importance of the proposed approach is twofold. First, while in the literature the waste collection problem is usually considered in the periodic settings (i.e., the dumpsters are forced to be visit periodically [9, 11]), the proposed approach removes this constraint . Second, the heuristic developed finds good solutions in a reasonable amount of time. For these reasons, the proposed approach has been adopted by the Cidiu Spa IT system.

The present paper is an extension of [6] including the exposition of the statistical model and the description of the IoT effects on the mathematical model. It is organized as follows: in Section 2, the waste collection problem is described, in Section 3 we revise the literature of the problem. In Section 4 we present the mathematical model, in Section 5 we describe the solution approach and in Section 6 we show the numerical results. Finally, in Section 7 we present the conclusion of the work and we depict future lines of research.

2 Problem description

Cidiu S.p.A. is a company dealing with environmental-services. It collects municipal waste in the towns of Alpignano, Buttigliera Alta, Collegno, Druento, Grugliasco, Pianezza, Rivoli, Rosta, San Gillio, and Venaria Reale (Figure 1). It is responsible for the collection of five types of waste: paper, solid urban refuse, plastic, metallic materials, and glass.

Cidiu S.p.A. is organized in two independent headquarters, one in Rivoli and one in Collegno. Each one of them manages the waste-collection operations in its area without interacting with the other one.

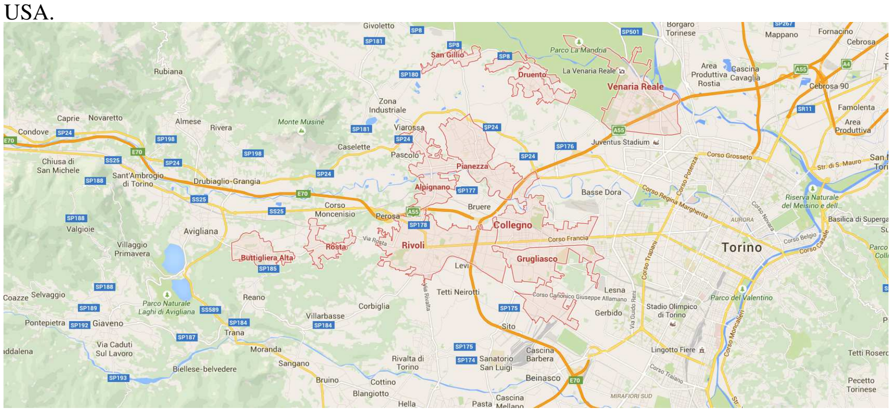
From Cidiu S.p.A. experience, each dumpster must be voided before it is 80 percent full.

The fleet of vehicles used to collect the waste is composed by 8 trucks (4 for each headquarter). Each vehicle must start its activity from one headquarter, travel to a predetermined set of dumpsters from which it collects waste, go to the dump, and return to the headquarter.

Each vehicle is equipped with an IoT sensor able to measure the weight of the dumpsters that it collects. This information can be exploited in several ways. First, it is possible to develop a statistical model for forecasting the daily increment of the waste quantity in each dumpster. Second, it is possible to monitor the production of waste and to react to sudden increments of production (e.g. the arrival of more people in a zone of the city).

Finally, it is possible to share the data with the population in order to improve the awareness of the waste collection activities. It is worthwhile noting that the

Fig. 1 The Municipalities Served by Cidiu S.p.A. Are Geographically Dispersed. Reprinted by permission, E. Fadda L.Gobbato, G.Perboli, M.Rosano, R. Tadei, "Waste Collection in Urban Areas: A Case Study", Interfaces, 48, 4, 2018. Copyright 2018, the Institute for Operations Research and the Management Sciences, 5521 Research Park Drive, Suite 200, Catonsville, Maryland 21228 USA.



vehicles are equipped with other IoT sensors such as the GPS tracking, sensors of the vehicle state, ecc. Nevertheless, we do not consider those sensors because they do not provide information useful for the optimization problem.

Cidiu S.p.A. organizes its operations in three time shifts. The first two are done in the morning (from 6 a.m. to 12 a.m.) and in the afternoon (from 1 p.m. to 7 p.m.); they have the same cost. Instead, the third time shift is more expensive and it is done during the night (from 10 p.m. to 4 a.m.). For this reason, one of the principal concern of Cidiu S.p.A. is to reduce the usage of the third time shifts.

The decisions that we want to optimize are how many vehicles to use in each time shift, which type of waste to collect and the list of dumpsters to visit.

The computation of the routing and scheduling must be computed in less than 6 hours (the duration of a time shift), in this way the Cidiu S.p.A. technical staff can check the solution and send it to the drivers.

It is important to remark that the problem description was obtained by using the GUEST methodology. This methodology allows people with different background to share their knowledge in a fast and easy way. We do not describe this methodology here because it is out of the topic (the interested reader is referred to [6]).

3 Literature review

The literature about waste collection and operation research is very wide. To the authors knowledge one of the most recent literature review about the topic is [7]. It classifies the literature in strategic, tactical, and operational decisions by considering the time horizon of the decisions. Strategic decisions deal with long range decisions such as building new facilities or buying new vehicles. Tactical decisions deal with medium range decisions such as dumpster locations. Instead, operational decisions deal with short range decisions such as the choice of day-to-day activities. The present paper belongs to this last branch. Due to its importance several works in this field have been done. The main stream of the literature about waste collection focuses in two problems: the computation of optimal routes for vehicles (see [11] and [4]) and the research for the optimal emptying frequency (see [8] and [9]). In particular, the papers dealing with this second problem compute the optimal emptying frequency of each dumpster and then they use this information in order to solve a periodic capacitated arc routing problem (e.g. [3]).

As stated above, we consider the problem of computing the scheduling and routing of waste collection, without imposing a fixed voiding frequency. Thus, we allow the solutions to define the time of a most suitable next visit to empty each dumpster. This approach has received less attention because companies often have agreements with the municipalities that involve fixed frequencies and because aperiodic solution needs a model of the growth rate of the waste in each dumpster.

Although the aperiodic approach is less explored in the literature, another study ([10]) not considering fixed routes is available. It presents a heuristic for applying the inventory-routing problem to waste collection, considering data from sensor-equipped containers.

Our study and that of [10] are different for several reasons. First, [10] considers a mathematical model addressing only vehicle routing decisions. Instead, our approach considers also the scheduling of the operations. Second, [10] uses sensor-equipped containers to forecast the level of fullness of each dumpster. This is, from the application point of view, a risky choice because the company must do the maintenance of all the dumpsters. Instead, having the sensors on the vehicles is more reliable and less subject to fault.

4 Mathematical formulation and solution method

Let $\mathscr{I}$ be the set of available vehicles, $\mathscr{S}$ the set of garbage types, $\mathscr{T}$ the set of time shifts and $\mathscr{J}$ the set of dumpsters. The cardinalities of these sets are I, S, J, and T, respectively. Without loss of generality we consider that the set $\mathscr{J}$ also includes the depot ($j = 1$) and the dumps ($j = J - S, \dots, J$ one for each type of waste). We use the following parameters:

- c_{it} is the cost of using vehicle $\forall\ i \in \mathscr{I}$ during shift $t \in \mathscr{T}$. This cost is the same for the first two time shifts and greater for the third shifts.
- $C_{\max}$ is the maximum duration of the time shift.
- $d_{j_1 j_2}$ is the time that the vehicle requires to go from dumpster $j_1 \in \mathscr{J}$ to dumpster $j_2 \in \mathscr{J}$.
- $\hat{C}$ is the maximum volume that a vehicle can transport.

- l_s is the difference between a standard quantity that a vehicle can transport and the real quantity if it is used to collect waste type $s \in \mathscr{S}$. This difference results from the use of a press (i.e., an engine that can compress the waste).
- Θ_{jt} is the increment of volume of waste in dumpster $j \in \mathscr{J}$ during time $t \in \mathscr{T} - 0$; Θ_{jt} is the quantity of waste in dumpster $j \in \mathscr{J}$ at the beginning of the first time shift.
- a is the time that the driver needs to collect the waste from a dumpster. Because of the technology installed on the vehicles, the collection time is the same for all dumpsters.
- α is the percentage of the dumpster volume that cannot be exceeded.
- λ is a parameter that weighs the importance of the routing with respect to the operational costs. It is expressed in €$/h$ and it considers the fuel cost and the manpower cost of the trip per hour.
- V_j is the capacity of dumpster j.

It is worthwhile noting that the parameters $\Theta_{jt}\ \forall\ t$ are computed by using the statistical models of the growth rate of the waste in each dumpster j. These models have been fitted by using the data recorded from the IoT sensors installed on the vehicles.

The following variables are used:

- w_{it} binary variables assuming value one if vehicle $i \in \mathscr{I}$ is used during shift $t \in \mathscr{T}$
- z_{ist}, binary variables assuming value one if vehicle $i \in \mathscr{I}$ collects the garbage of type $s \in \mathscr{S}$ during shift $t \in \mathscr{T}$,
- y_{ijt}, binary variables assuming value one if vehicle $i \in \mathscr{I}$ collects the garbage of dumpster $j \in \mathscr{J}$ during shift $t \in \mathscr{T}$
- $r^{it}_{j_1 j_2}$, binary variable assuming value one if vehicle $i \in \mathscr{I}$ during time shift $t \in \mathscr{T}$ goes from dumpster $j_1 \in \mathscr{J}$ to dumpster $j_2 \in \mathscr{J}$.
- x_{ijt}, continuous variables describing the volume of garbage collected by vehicle $i \in \mathscr{I}$ from dumpster $j \in \mathscr{J}$ during shift $t \in \mathscr{T}$,
- V_{jt}, continuous variables describing the volume of waste present in dumpster $j \in \mathscr{J}$ at the end of time shift $t \in \mathscr{T}$.

The mathematical problem describing Cidiu's activities is:

$$\min \sum_{i=1}^{I} \sum_{t=1}^{T} c_{it} w_{it} + \lambda \sum_{i=1}^{I} \sum_{t=1}^{T} \sum_{j_1=1}^{J} \sum_{j_2=1}^{J} d_{j_1 j_2} r^{it}_{j_1 j_2} \tag{1}$$

subject to

$$w_{it} \geq y_{ijt} \quad \forall\ \ i, j, t \tag{2}$$

$$M y_{ijt} \geq x_{ijt} \ \ \forall\ i, j, t \tag{3}$$

$$\sum_{i=1}^{I} y_{ijt} \leq 1 \ \ \forall\ j, t \tag{4}$$

$$x_{ijt} \geq V_{jt} - M(1 - y_{ijt}) \quad \forall\ i, j, t \tag{5}$$

$$\sum_{j=1}^{J} x_{ijt} \leq \hat{C} + \sum_{s=1}^{S} l_s z_{ist} \quad \forall\ \ i, t \tag{6}$$

$$M z_{ist} \geq x_{ijt} \ \ \forall\ i, s, j \in \mathscr{J}^s, t \tag{7}$$

$$\sum_{s=1}^{S} z_{ist} \leq 1 \ \ \forall\ i, t \tag{8}$$

$$V_{j0} = \Theta_{j0} \ \ \forall\ j \tag{9}$$

$$z_{ist} \leq y_{i(J-s)t} \ \ \forall\ i, t \tag{10}$$

$$V_{jt} = V_{jt-1} + \Theta_{jt} - \sum_{i=1}^{I} x_{ijt} \quad \forall\ j, t \neq 0 \tag{11}$$

$$V_{jt} \leq \alpha V_j \quad \forall j, t \tag{12}$$

$$w_{it} \geq w_{i+1,t} \ \ \forall\ t, i = 1 : I - 1 \tag{13}$$

$$\sum_{j_1=1}^{J} r^{it}_{jj_1} = y_{ijt} \ \ \forall\ t, i, j \tag{14}$$

$$\sum_{j_1=1}^{J} r^{it}_{jj_1} = \sum_{j_1=1}^{J} r^{it}_{j_1 j} \ \ \forall\ t, i, j \tag{15}$$

$$\sum_{j=1}^{J} r^{it}_{1j} = w_{it} \ \ \forall\ t, i \tag{16}$$

$$\sum_{j=1}^{J} r^{it}_{j1} = w_{it} \ \ \forall\ t, i \tag{17}$$

$$\sum_{j_1=1}^{J} \sum_{j_2=1}^{J} d_{j_1 j_2} r^{it}_{j_1 j_2} + a \sum_{j=1}^{J} y_{ijt} \leq C_{\max} \ \ \forall\ i, t \tag{18}$$

$$\sum_{j_1, j_2 \in S, j_1 \neq j_2} r^{it}_{j_1 j_2} \leq |S| - 1 \ \ \forall S \subset \mathscr{J}, S \neq \emptyset \tag{19}$$

$$x_{ijt} \in \mathbb{R}^+ \quad \forall i, j, t$$
$$z_{ist} \in \{0, 1\} \quad \forall i, s, t$$

$$y_{ijt} \in \{0,1\} \quad \forall i,p,t$$
$$r^{it}_{j_1 j_2} \in \{0,1\} \quad \forall i,j_1,j_2,t$$
$$V_{jt} \in \mathbb{R}^+ \quad \forall j,t$$

The objective function is the weighted sum of the costs derived from the usage of a vehicle during a time shift and the routing cost. Constraints (2) and (3) are logic constraints enforcing that it is not possible to use a vehicle during a time shift, without activating the corresponding time shift. Constraints (4) enforce that, in each time shift, no more than one vehicle can void a dumpster. Constraints (5) enforce that the vehicles must collect all the garbage from the dumpsters it visits. Constraint (6) enforces the capacity limit of the vehicles; the right hand side considers that for some types of waste the vehicle can press the waste, thus diminishing the volume. Constraints (7) and (8) enforce that vehicles cannot collect waste from dumpsters of different type. Constraints (10) enforce that if a vehicle is used for voiding waste type $s \in \mathscr{S}$, it must go to the assigned dump. Constraints (9), (11), and (12) enforce the model of the evolution of the waste in each dumpster and bound this quantity. Constraints (13) enforce an order in the vehicle choice. These constraints are used for breaking the symmetry of the problem by reducing the feasible set. Finally, constraints (14), (15), (16), (17), (18), and (19) describe the routing problem and set a maximum time for the activity.

It is worth noting that because of constraints (9) and (11) the value of V_{jt} can be modified only by using the variables x_{ijt}. Furthermore, if variables variables x_{ijt} are null, then constraint (12) is violated because the contributions $\Theta_{jt} > 0 \forall j,t$.

4.1 The statistical model

For each dumpster, the company records the waste quantity collected. We call $\hat{\theta}_{jn}$ the observed quantity of waste collected from dumpster j during the collection n, θ^p_{jn} the corresponding random variable, and t_n the time (expressed in number of time shift) of the n-th collection. Given a waste producer p belonging to the set of waste producers $\mathscr{P}$, we call the quantity of waste produced by p in dumpster j and collected during the collection n as θ^p_{jn}. It holds that

$$\theta_{jn} = \sum_{p \in \mathscr{P}} \theta^p_{jn} \tag{20}$$

We assume that the quantity of waste observed in each dumpster is produced uniformly in time. Furthermore, we suppose that the distributions of the $\hat{\theta}^p_{jn}$ have finite mean and variance and that the random variables $\hat{\theta}^p_{jn}$ are independent. Furthermore, we assume that the Lyapunovs condition holds, i.e., there exists $\delta > 0$ such that

$$\lim_{n\to\infty} \frac{1}{s_n^{2+\delta}} \sum_{i=1}^{n} \mathbb{E}\left[|\theta^p_{jn} - \mu_{jn}|^{2+\delta} \right] = 0, \tag{21}$$

where μ_{jn} and s_n are respectively the average and the square root of the sum of the variances of the θ^p_{jn}.

The Lyapunovs condition guarantees that the moments of the distributions do not increase too much as it is reasonable to assume. By applying the Lyapunov central limit theorem [2], we have that the θ_{jn} are normal distributed random variables. Thus, we use as estimator for the production rate the average daily fulfillment rate:

$$\Theta_{jt} = \frac{1}{N}\sum_{n=1}^{N}\frac{\hat{\theta}_{jn}}{(t_n - t_{n-1})}\ \forall j,t.$$

5 The Solution Algorithm

The mathematical model described in (1)-(19) is a mixed-integer linear problem. Thus, the main method to solve the problem exactly is the branch and bound algorithm. Since the number of variables of the model is $\mathscr{O}(2^{IJ^2T})$ (where I is the number of vehicles, J is the number of dumpsters, and T is the number of time steps) this is also the worst case complexity of the model. It is easy to see that even for small-size problems the number of variables is big. In order to overcome this problem we implement a heuristic method. Based on numerous experiments, we decided to use a three-phased heuristic. We describe the first phase is Subsection 5.1 and the two remaining phases in Subsection 5.2.

5.1 Clusterization

Phase 1 solves the exact problem by considering aggregation of dumpsters (called clusters), instead of single dumpster. The policy chosen for aggregation is geographical proximity i.e. we group together all the dumpsters located in the same city. This choice greatly outperforms other kinds of policy such as grouping together the dumpsters by level of productivity, last visit date, etc. We cannot present the comparison between the different methods in this paper for length constraints. It is worthwhile noting that, in order to solve the exact problem with clusters instead of dumpsters, we have to modify model (1)-(19). In particular, instead of the set $\mathscr{J}$, we consider the set $\mathscr{C}$, the set of clusters (with cardinality C). We remove constraints (4) and (5), because we allow more than one vehicle to collect waste from the same cluster. This choice increases the size of the feasible solution space and ensures the feasibility of the problem. In fact, since we consider a low number of clusters and a vehicle has enough time to visit at least one cluster, the worst feasible solution is that each vehicle collects exactly one cluster.

Moreover, in the new model the parameter $d_{c_1c_2}$ becomes the distance between cluster c_1 and cluster c_2, Θ_{ct} becomes the maximum growth rate of the dumpsters in the cluster, V_c the capacity of the cluster and $\hat{a}_C$ becomes the time spent to empty a cluster. We define them as follows:

1. $d_{c_1c_2} = \min_{j_1\in c_1 j_2\in c_2} d_{j_1j_2}$;
2. $\Theta_{ct} = \max_{j\in c} \Theta_{jt}$;
3. $V_c = \max_{j\in c} V_j$. V_c is the maximum capacity of the dumpsters in the cluster;
4. $\hat{a}_C = T_v(C) + T_r(C)$ where $T_v(C)$ is the sum of the emptying time of all dumpsters and $T_r(C)$ is the time of a path among all dumpsters in the cluster.

Remark 1 *It is worthwhile noting that the parameter $\hat{a}_C$ used in the cluster model is the sum of the time for visiting all dumpsters in the clusters plus their emptying time. In other words, it represents the worst possible case i.e. the one in which all dumpsters in the clusters must be voided. We choose this very conservative value because, in the cluster model, $d_{c_1c_2}$ is a lower approximation for the travelling time and by that choice we ensure that for each travelled edge (c_1, c_2) the sum $\hat{a}_{C_1} + d_{c_1c_2} + \hat{a}_{c_2}$ is an upper bound of the total time spent for the collection.*

On average, the trip time computed in the cluster model is 1.5 times the one computed in the real model. Nevertheless, since the critical resource of the problem is the volume of the vehicle, this approach does not remove any feasible solution from the solution space.

5.2 Building a feasible solution and Postoptimization

By using the solution computed in the Phase 1, Phase 2 builds a feasible solution for problem (1)-(19). Its output is, for each vehicle and for each time shift, a list of dumpsters that the vehicle must void. The procedure is shown in the following Algorithm (1).

Data: Solution of the model (1)-(19) for the cluster network
Result: Solution of the model (1)-(19) for the real network
for *each* $w_{it} = 1$, *where* $i \in \mathscr{I}$, $t \in \mathscr{T}$ **do**
  create list *list0*;
  insert in *list0* all dumpsters for each cluster, such that $y_{ict} = 1$ where $i \in \mathscr{I}$, $c \in \mathscr{C}$, $t \in \mathscr{T}$;
  remove from *list0* all dumpsters that have been voided in the previous iterations;
  sort *list0* in decreasing order of quantity of waste;
  create *list1*;
  while *Constraints (6) or (18) computed on list1 hold with equality and list0*$\neq \emptyset$ **do**
    add, the first element of *list0* into *list1*;
    remove the first element of *list0* ;
  end
  if *list0*$= \emptyset$ **then**
    add all the dumpsters that are such that if voided the time of the path as well as the capacity of the vehicle is not exceed;
  end
end

Algorithm 1: Post Optimization

From the solution provided by Algorithm 1, Phase 3 optimizes the routing. In particular, for each list of dumpsters that a vehicle has to void during a time shift, it computes the solution of a traveling salesman problem (TSP) by using the Chained-Lin-Kernighan heuristic for asymmetric networks, as [1] discusses.

Because the Phase 1 and Phase 2 run quickly, we run them several times by randomly changing the order in which the dumpsters in *list0* are ordered.

Remark 2 *It is worthwhile noting that the variables* z_{ist} *are set by the association of a vehicle to a type of waste and they are derived from the exact solution of the clusterized model.*

6 Computational experiments

In order to evaluate the solutions provided by the heuristic, we considered six key performance indicators (KPIs):

- nTS: average number of third shifts used during a week of activity.
- nV: average number of vehicles daily used. This KPI is the ratio between the number of vehicles used during one month of activity and the number of days.
- WV%: average percentage of waste volume at the moment of collection. During the collection operations, the vehicle records the volume occupied by the waste. The indicator is computed by averaging the percentage of occupation over all the collections and all the dumpsters collected;

- TRT: total routing time.
- FV%: average fulfillment percentage of the vehicles. This KPI is the average percentage of fulfillment over each time shift and over each vehicle.
- nVD: average number of dumpsters visited during each time shift in which a vehicle is used.

In Table 1 we show the KPIs values for a real month of activity for Cidiu S.p.A. and a simulated month of activity for the proposed method (within brackets the standard deviation of each value is shown). The simulated month is the same as the real one.

Table 1 For Each KPI, We Compare the Solution before and after Using Our Proposed Algorithm

KPIs	Cidiu S.p.A. solution	Simulated solution
nTS	1.44 (0.5)	0 (0)
nV	3 (0)	2 (0)
WV%	0.28 (0.10)	0.70 (0.05)
TRT	4.35 (0.5)	5.24 (0.3)
FV%	54%(10%)	87%(5%)
nVD	62.3(12)	68.5(12)

The results presented in Table 1 show that the proposed methodology outperforms the actual policy with respect to all the KPIs. The most important result is that the proposed method do not use the third shift. Furthermore, it uses 33% less vehicles. It is worthwhile noting that the increase in the total routing time is due to the usage of fewer vehicles that have to travel more. For this reason, the growth of the total routing time is not due to inefficiency but it denotes a better usage of the vehicles.

In order to test the effects on the real field of the algorithm, Cidiu S.p.A. uses the methodology for small periods of time obtaining similar results to the ones in the simulation. Currently, due to the good results, Cidiu S.p.A. is integrating the proposed methodology into its IT system.

It is important to note that the problem depends by the parameter λ that converts the time of the routing in cost for the company. Unluckily, it is difficult to estimate because it is generated by fuel consumption, the cost of the drivers, the depreciation of the vehicle, etc. Nevertheless, variations in the value of this parameter change slightly the solution. Another parameter that does not influence the solution is the capacity of the vehicle $\hat{C}$. This is due to the fact that the most critical resource is the duration of the time shift and not the volume of the vehicle.

Instead, the model is sensitive to changes in the Θ_{jt}. The greater those quantities the greater the total cost. It is worthwhile noting that for Θ_{jt} sufficiently high the model becomes unfeasible. By this mathematical observation, it is possible to deduce the importance of the data recorded by the IoT sensors measuring the weight of the refuse. An accurate estimation of the waste collection production leads the model to be really effective. Indeed, this is an added value of the proposed methodology that, to the authors knowledge, has never been considered in the literature.

Another parameter that deeply influences the model is the duration of the time shift $C_{\max}$. The greater this value, the lower the objective function.

In order to estimate the optimality gap of the solutions obtained by the proposed heuristic, we compared them with the optimal solution found using CPLEX 12.6. Since the solver is not able to solve real instances because it runs out of memory, we consider instances with $10, 20, 30, 40$, and 50 dumpsters, six time periods, and two types of waste.

In those instances, the dumpsters are spatially generated from a combination of multinomial distributions, in order to be located in scattered ellipses (as in the real settings). The initial waste quantity of each dumpster and its increment are simulated from the historical data. The travel times are computed by using the real distances and the costs of each time shift are the same as the one of Cidiu S.p.A.

Table 2 shows the results of this comparison, we report the differences between the costs of time shifts and the costs of the routing of the two solutions. In each cell the table shows the average value over 20 runs and standard deviation (in brackets).

Table 2 The Table shows a Comparison of Cidiu S.p.A.'s Optimal Solutions and the Solutions Generated Using our Proposed Approach

Number of dumpsters	nTs [%]	rC [%]	Optimal time [s]	Heuristic time [s]
10	0 (0)	0(0)	43.43 (1.64)	2.76 (0.65)
20	0 (0)	0(0)	150.43 (10.89)	3.73 (0.56)
30	0 (0)	1.75 (1.38)	443.64 (15.92)	8.56 (0.84)
40	0 (0)	2.69 (1.43)	890.67 (30.53)	13.36 (0.74)
50	0 (0)	3.32 (2.34)	1842.86 (45.65)	26.27 (2.45)

It is worthwhile noting that the proposed method finds the optimal number of time shifts in all the generated instances. The differences between the optimal solution and the one found by the heuristic are in the routing.

Furthermore, the average running time of the proposed method in the real setting is 4 hours and 23 minutes with a standard deviation of 20 minutes (these values are computed by using 100 simulations).

Thus, the proposed heuristic can be run once every time shift, allowing the management to adjust the plan and to consider missed operations (e.g., the vehicle cannot collect the waste because a car is parked near the dumpster).

7 Conclusions

In conclusion, we claim that the proposed method has proven to be effective in the real field: the system presented is currently being integrated into the IT system of Cidiu S.p.A. and, according to the company forecasts, the system will be fully operational by the end of 2018. By doing so, we have proved that the aperiodic approach is worth to be studied and that heuristics dealing with this problem can be useful in real world.

References

1. Applegate, D., Cook, W., Rohe, A.: Chained lin-kernighan for large traveling salesman problems. INFORMS J. Comput. **15**(1), 82–92 (2003)
2. Billingsley, P.: Probability and Measure. John Wiley & Sons, Inc., New York, NY, USA (1995)
3. Chu, F., Labadi, N., Prins, C.: A scatter search for the periodic capacitated arc routing problem. Eur. J. Oper. Res. **169**(2), 586–605 (2006)
4. Das, S., Bhattacharyya, B.: Optimization of municipal solid waste collection and transportation. Waste Management **43**, 9–18 (2015)
5. European Environment Agency: http://www.eea.europa.eu/soer-2015/countries-comparison/waste. Accessed July 27, 2016 (2015)
6. Fadda, E., Gobbato, L., Perboli, G., Rosano, M., Tadei, R.: Waste collection in urban areas: A case study. INTERFACES **48**(1), 103–120 (2018)
7. Ghiani, G., Laganà, D., Manni, E., Musmanno, R., Vigo, D.: Operations research in solid waste management: A survey of strategic and tactical issues. Comput. Oper. Res. **44**, 22–32 (2014)
8. Hemmelmayr, V., Doerner, K., Hartl, R., Vigo, D.: Models and algorithms for the integrated planning of bin allocation and vehicle routing in solid waste management. INFORMS Transportation Sci. **48**(1), 103–120 (2013)
9. Mansini, R., Speranza, M.: A linear programming model for the separate refuse collection service. Comput. Oper. Res. **25**(8), 659–673. (1998)
10. Mes, M., Schutten, M., Rivera, A.: Inventory routing for dynamic waste collection. Waste Management **34**(9), 1564–1576 (2014)
11. Sahoo, S., Kim, S., Kim, B., Kraas, B., Popov, A.: Routing optimization for waste management. Interfaces **35**(1), 24–36 (2005)